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Noise Cancellation Model Validation for Reduced Motion Artifact Wearable PPG Sensors Using MEMS Accelerometers

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Abstract—**This paper investigates the validity of utilizing Widrow's Active Noise Cancellation (ANC) in the context of motion artifact reduction for photoplethysmogram (PPG) sensors. The ANC approach has previously been applied to the PPG problem, but little consideration has been given to the validity of the ANC signal corruption assumptions and in what motion range the algorithm works. The ANC validity testing is done in the form of impact (approximate impulse) testing of the physical PPG system and comparing with the modeled response for a range of motion amplitudes. The testing reveals that the identified corruption model does not generally represent the true physical system, but locally approximates the true system. Testing shows that if a similar motion amplitude is used for model tuning as the impact test, an average peak deviation of 5.2% is obtained, but if a motion amplitude that is smaller than the impact amplitude by a factor of 5, the peak deviation is 15%. Finally, after ANC filtering motion corrupted data, heart rate can be estimated with less than 1.6% error.**

I. Introduction

Wearable medical sensors are expected to be revolutionary in many clinical areas, ranging from home health monitoring to sports medicine and battle field monitoring [1]. The photoplethysmograph (PPG) sensor, in particular, contains rich information about heart pulsation and blood oxygen saturation as well as breath rate [2]. Wearable PPG sensors have the potential to monitor a broad range of health determinants in a compact sensor unit, allowing patients to wear the sensor for extended periods without interfering with their daily lives or duties. Despite the salient health monitoring capability found in PPG sensors, the information they gather is known to be susceptive to motion induced corruption, making them unreliable health indicators unless the wearer is stationary [3]. Therefore, it is a crucial requirement that wearable PPG sensors be robust against corruption during wearer motion. Since a ring cannot be rigidly fixed to a human finger and a finger is inherently deformable, the motion artifact cannot be eliminated, but must be removed after the fact.

Many noise reduction techniques are available, ranging from bandpass filtering to independent component analysis [4]. However, in the case of a PPG ring sensor, noise is in-band (precluding bandpass filtering) and the motion-to-noise relationship can rapidly vary (independent component analysis and other methods using higher order statistics are not rapidly tunable). Widrow's Active Noise Cancellation [5] is capable of removing in-band disturbances and, because it is based on a second order statistic, can rapidly adapt to any sensor attachment variations or other system changes. This method requires a noise reference and assumes that the artifact induced within the measured signal is uncorrelated with the desired signal, but requires nothing else of the relative frequency content of the desired and artifact signals.

For motion artifact cancellation, accelerometers are a natural choice for motion reference. Accelerometers are also convenient because they are already used for daily monitoring of the elderly, rehabilitation patients, and Chronic Obstructive Pulmonary Disease patients, among many uses [6, 7].

Accelerometers have previously been suggested as motion references in the active noise cancellation framework for biosignals by [8], [9], and [10]. Reference [8] used accelerometers placed at ECG electrodes to measure local disturbances, obtaining up to a 91% mean squared error reduction, where [9] used accelerometers placed at the lower back to measure bulk motion for running/jogging stress test patients and showed a significant improvement in ECG waveform consistency between heart beats. Finally, Relente in [10] used an accelerometer as a motion reference for removing artifact from a Nellcor pulse oximetry sensory.

Common to all of these previous implementations is the adoption of the active noise cancellation (ANC) corruption model without consideration for how the physical system is actually corrupted. The corruption model assumed in the ANC framework may not be representative of the true physical system. This means that a long filter order (32 parameters in [10]) is required to describe the disturbance system using the ANC model. Long filter orders require richly exciting disturbance inputs to correctly identify all of the parameters. If the ANC model is, in fact, inappropriate, then it locally approximates the true system, meaning that it must quickly adapt to different disturbance types, and quick adaptation is difficult to achieve when a large number of parameters need to be tuned.

This work investigates the function of Widrow's Active Noise Cancellation in the context of a ring-type PPG sensor [3]. It begins by analyzing the inherent assumptions in the ANC framework, then poses a series of impact (approximate impulse) experiments to determine how well the ANC model represents the physical system. Additionally, the impact

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testing reveals that the system response has a slow dominant pole, which can be modeled using the Laguerre basis function to reduce the required filter order. Final testing shows that ANC filtered motion corrupted data provides high accuracy heart rate estimation.

II. Wearable PPG Sensors and Motion Artifact

A. Finger PPG Physics

The focus of this work is on motion artifact in a ring-type PPG sensor proposed and utilized by [3]. A ring PPG sensor is held in place at the base of a finger by a band. Figure 1a shows a cross sectional view of the PPG physical function. The band of the ring sensor has an embedded photodetector (PD) and a photoemitter (an LED). The ring sensor measures volume fluctuations in the digital artery by emitting a constant intensity light from the LED into the finger and measuring the intensity absorbed at the PD. Figure 1b shows a tightly fixed ring sensor with attached accelerometer for motion reference utilized in all experiments in this work.

In normal ring sensor use, the objective is to determine heart induced variation of blood volume in the digital artery via PD light intensity variations. However, when the wearer is in motion, other factors contribute to the intensity measurements:

- Ambient light intensity variation
- LED and PD skin contact angle/pressure variation
- Motion induced blood flow and tissue reshaping

Ambient lighting artifact is easily resolved using LED modulation and the hope is that, by using the experimental setup in Fig.1b, where an external wrap securely fixes the sensor attachments to the skin, the sensor contact disturbances are not discontinuous and can be modeled. The rest of this work will show ANC's capability of identifying the composite affect of sensor contact and blood/tissue inertial affects.

III. Modeling and Identification of Motion Corruption Processes

A. Framework for Active Noise Cancellation

Figure 2 shows a basic block diagram for active noise cancellation discussed presently. The primary heart signal source, $y_h(t)$, is not measurable, but the motion corrupted PPG, $y(t)$, is measured from a ring PPG sensor. A MEMS accelerometer is attached to the ring sensor to measure the acceleration, $a(t)$, of the hand to which the ring sensor is attached (see Fig. 1b). Note that, in this framework, we only consider bulk motion along the axis of the finger. This is acceptable because experimentation shows that bulk motion in other directions has little affect on the measured PPG signal. The recovered signal, $\hat{y}(t)$ is obtained by tuning the motion-to-noise filter, $\hat{h}(t)$ such that $\hat{y}(t)$ is uncorrelated with $a(t)$.

With the uncorrelation assumption, and assuming a FIR filter, a parameter tuning formulation can be cast in the discrete time domain in matrix format as an exponentially weighted least squares problem [11] :

$$\frac{1}{N}\sum_{t=1}^{N}\left[\eta^{N-t}\underset{\sim}{a}^{T}(t)\underset{\sim}{a}(t)\right]\underset{\sim}{\hat{h}}=\frac{1}{N}\sum_{t=1}^{N}\left[\eta^{N-t}y(t)\underset{\sim}{a}(t)\right] \quad (1)$$

where $\underset{\sim}{\hat{h}}=\left[g_1\cdots g_n\right]^T$ are the tuned parameters, $\underset{\sim}{a}(t)=\left[a(t-1)\cdots a(t-n)\right]^T$, n is the length of the FIR filter and $0\le\eta\le1$ is the forgetting factor, with no forgetting when $\eta=1$. When cast recursively, the previous equation represents active noise cancellation for this problem.

B. Assumptions in Active Noise Cancellation

The corruption model presented in Fig. 2 was selected because it allows for solution of the unknown model parameters, $\hat{h}(t)$, but is this model actually capable of describing the physical corruption system?

The model implicitly makes two assumptions about the PPG corruption (excluding the correlation condition required to obtain Eq. (1)):

- *Linearity*: motion to PPG noise relationship, $h(t)$, responds linearly to a local set of motion inputs
- *Additivity*: motion induced light intensity variation, $w(t)$, *adds* with the heart induced light intensity variation, $y_h(t)$, to create the measured PPG signal, $y(t)$.

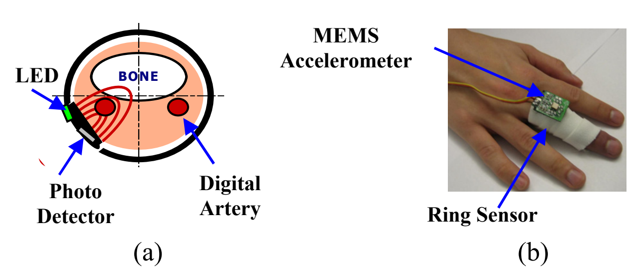

Figure 1: Cross-sectional diagram of the PPG ring sensor (a) and experimental ring sensor with accelerometer (b).

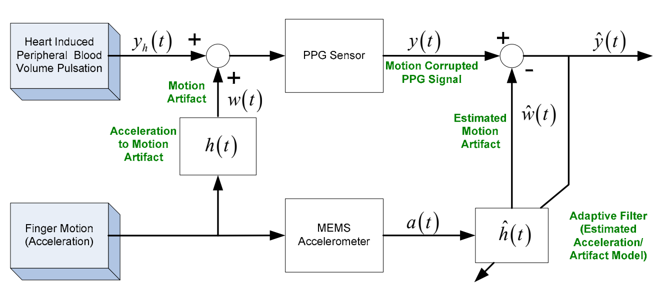

Figure 2: Active Noise Cancellation framework using MEMS accelerometer as motion reference.

Linearity is a desirable characteristic so that, regardless of the magnitude or frequency content of the input signal, the model should remain invariant. However, in the actual system, the measured light intensity varies exponentially with the distance traveled through the absorbing medium, as given by the Beer-Lambert law. Also, it is unclear exactly how motion affects blood volume changes in the finger, which could be a nonlinear process.

The additivity requirement is important in deriving the ANC result, but is it appropriate? The arterial walls and surrounding tissues are compliant and the non-pressure head induced blood flow is influenced by many factors. How is the blood and tissue being redistributed under inertial affects, and how are these affects superimposed on the true heart signal, $y_h(t)$? It is not clear that superposition holds.

It is possible that neither linearity nor additivity are representative of the true physical system. However, *since $\hat{h}(t)$ is adaptively computed assuming both linearity and additivity, it should locally approximate the true system* over a range of disturbance conditions. The question is: how large is the approximation error for different motion types?

C. Structure for Corruption Model Validation

Since the affects of additivity and linearity are composite in the motion corrupted signal, it is not possible to show that each one holds separately. A persistently exciting input is required to estimate $\hat{h}(t)$, while an impact (approximate impulse) test is a good way to evaluate the experimental and model responses. Despite the complications in identifying additivity and linearity independently, the pertinent question with regard to model function is: *does the physical system response to a motion impulse match the model proposed by Fig. 2, for each disturbance the sensor may experience?* The implication is that only consistency is required between the model and the physical system for a localized input type.

For correct filter identification, it is required that a range of frequency content is present in the input. Thus, for validation, we will distinguish different input types by acceleration amplitude only, acknowledging that each model must predict correctly for a range of frequency content in the input.

We are looking to verify that the model approximates the disturbed signal for a range of inputs. That is, for each input considered:

$$\begin{gathered} Model \approx Validation\ Data \\ \Rightarrow y_h(t) + \hat{h}(t) * a(t) \approx y(t) \end{gathered} \tag{2}$$

The input acceleration, $a(z)$, and true PPG sensor response, $y(z)$, are measurable, and the transfer function, $\hat{h}(t)$, is easily found using the noise cancellation framework on sufficiently excited data just prior to the impact.

The most difficult quantity to obtain is the true heart signal, $y_h(t)$, in the motion corrupted impact window. To obtain the desired true heart data, we resort to using two ring PPG sensors: one placed on the left hand, which remains stationary, and the other on the right hand, which is impacted by the hand acceleration.

The stationary ring sensor provides information about how the heart is beating – independent of motion artifact. However, the positioning and loading of each ring sensor is different, causing differences in beat morphology. Thus, $y_h(t)$, must be found from the motion corrupted hand.

The true heart beat can be interpolated by using the morphology information of several clean beats immediately prior to the impact from the motion corrupted hand with the timing and amplitude information gleaned from the stationary sensor. The beat interpolation procedure is as follows:

- Choose several beats prior to the impact
  - Normalize with respect to time
  - Average beat waveform over time
- Guide average beat by stationary PPG
  - Time scale using peak from stationary PPG
  - Linearly shape averaged beat to track relative amplitude fluctuations in stationary PPG

IV. Model Validation Results

The Massachusetts Institute of Technology Committee On The Use of Humans as Experimental Subjects (Approval No. 3117) has approved the use of the ring sensor and accelerometer utilized in all experiments in this work.

A series of impact tests were performed at different acceleration amplitudes from 0.4-2.0G, incremented by 0.4G, to evaluate the model effectiveness. Each test was performed 5 times and the results averaged. For these experiments, we selected an order 20 FIR model, $\underset{\sim}{\hat{h}}(t)$, at 100Hz sampling rate and a forgetting factor of 0.998. Initial experimentation has shown that FIR models with greater than 20-30 FIR parameters provide negligible improvements in error, (when comparing a motion recovered signal with a stationary PPG signal). Approximately 20sec segments of sufficiently exciting data were used to identify the model parameters. Motion stops approximately 5sec prior to the impact to allow any remnant motion energy to decay.

Figure 3 shows how the heart signal, $y_h(t)$, is identified in the motion corrupted region for a particular 2G impact test. First, a series of heart beats are identified, in the *Averaged Beats* box, and averaged. Next, the region of motion corrupted data is identified and guidance beats are selected from the stationary sensor, in the *Guidance Beats* box.

Figure 4 shows the estimated disturbance, which was determined using the recently identified $\underset{\sim}{\hat{h}}$ and the measured acceleration. The estimated disturbance is added to the heart signal to obtain the modeled corrupted PPG signal. From Fig. 4, the model appears to capture the waveform shape in the impacted region.

Model performance for each experiment was evaluated in two ways. First, the mean squared error (MSE) was computed between the estimated disturbance, $\hat{w}(t)$, and the experimental disturbance found by subtracting the interpolated PPG from $y(t)$. The second evaluation mode was to compute the deviation of the modeled disturbance from the experimental disturbance at the experimental disturbance peak. To ensure comparability between different experiments, the experimental impact response was scaled to have amplitude 1, and the peak deviation is given as percent of the experimental peak amplitude.

From Table I, the peak deviation is a small fraction of the impulse amplitude and the MSE is small for all amplitudes. The MSE, however, is not completely instructive because, as can be seen in Fig, 4, there is large error at the disturbance peak but little error elsewhere. It should be noted that larger MSE for smaller acceleration amplitudes is due to a poorer phase matching. As an indication of why the adaptive parameter method is so important, impact testing where the input amplitude for identifying $\hat{\underline{h}}$ is 0.4G but the impact amplitude is 2G yields an average MSE of 0.08 and a percent peak deviation of 15%.

These tests indicate that the noise cancellation approach is amenable to the PPG motion artifact problem, but that adaptation is necessary so that the linear model can everywhere locally approximate the true system. Further,

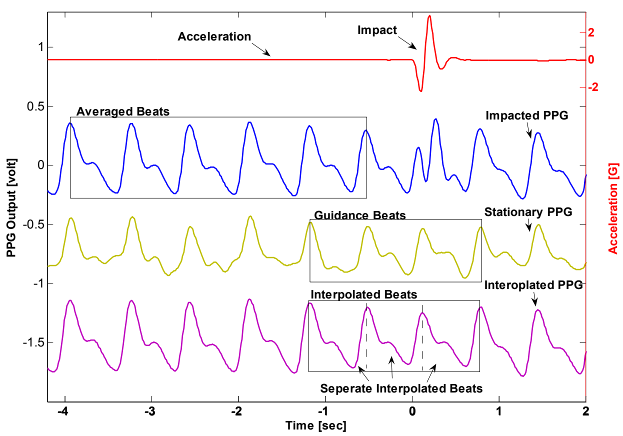

Figure 3: Beat interpolation by averaging undistorted beats prior to impact and guiding average beat by stationary PPG beats in motion corrupted region.

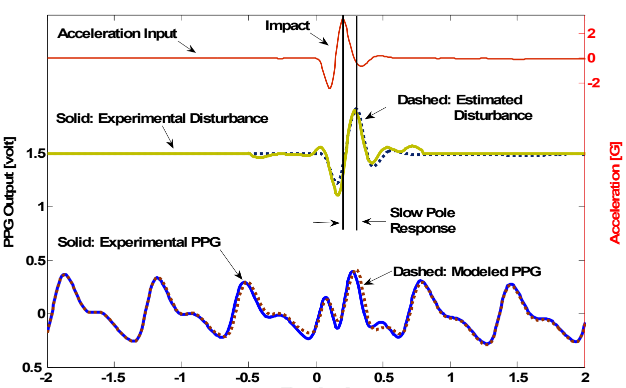

Figure 4: Modeled PPG corruption compared with experimental PPG corruption.

TABLE I

AVERAGE MSE AND PERCENT DEVIATION VS. AMPLITUDE.

Accel. Amp. [G]	0.4	0.8	1.2	1.6	2.0
MSE	0.192	0.139	0.0205	0.0200	0.0206
% Deviation	1.4	2.1	6.2	6.0	10.4

this adaptation requirement indicates that a small number of tunable parameters should be used. The long impact decay time shown in Fig. 4 indicates that a slow pole model, such as the Laguerre basis function, can be used to reduce the number of tunable parameters and improve filter performance.

As a final test, heart rate estimation was conducted on motion corrupted PPG signals from the second half of each parameter training data segment from the impact testing. Four parameter Laguerre based ANC was utilized to estimate the true signal and then heart rate was estimated by computing a windowed frequency spectrum and labeling the highest peak as the heart frequency. When compared to the stationary hand, heart rate was estimated with less than 1.6% error for all trials. Without the ANC filter, heart rate was always determined to be the motion frequency of greatest power when the motion power was greater than the heart power. This can lead to heart rate estimation with greater than 100% error, depending on the motion frequency of the wearer.

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